

A Recent Perspective on Predictive Computational Science: Educational Needs and Opportunities

Eric Phipps

Optimization & Uncertainty Quantification Department
Sandia National Laboratories
Albuquerque, NM USA
etphipp@sandia.gov







Outline

- Overview of driving forces behind computational science at Sandia National Labs
- Predictive computational science
 - Verification
 - Uncertainty Quantification
 - Validation
- Automatic differentiation as a vehicle for transformation to predictive science
- Educational needs and opportunities



Brief Overview of Sandia National Labs

- Founded in 1945 during the Manhattan Project
 - Primary mission was to design, produce and test all non-nuclear components of nuclear weapons
 - Security systems
 - Arming and fuzing systems
 - Safety systems
 - Instrumentation
 - Parachute systems and aerodynamic design



- Labs are located in Albuquerque, NM and Livermore, CA
 - Employ approx. 8,500 people (18% PhD)
- Managed by Sandia Corporation, a subsidiary of Lockheed Martin Corporation, for the National Nuclear Security Administration (NNSA, part of DOE)
 - Lab employees are DOE contractors



Sandia Has Many Diversified Missions

- Nuclear Weapon Stockpile Stewardship
 - Ensure the stockpile is safe, secure, reliable, and can support the United States' deterrence policy
- Nonproliferation and Assessments
 - Reduce the proliferation of weapons of mass destruction, the threat of nuclear accidents, and the potential for damage to the environment
- Military Technologies and Applications
 - Address new threats to national security
- Energy and Infrastructure Assurance
 - Enhance the surety of energy and other critical infrastructures
- Homeland Security
 - Help protect our nation against terrorism



NW Stockpile Stewardship is Sandia's Primary Mission

- Weapons are currently no longer produced
- Sandia's primary mission is to ensure the existing stockpile is
 - Safe
 - Ensure weapons don't detonate after an accident (plane crash, fire, etc...)
 - Secure
 - Ensure weapons cannot be detonated without authorization
 - Reliable
 - Ensure there is no degradation of performance over time
- Sandia does yearly testing to assess and certify the stockpile
 - Destructively and non-destructively test individual components and systems of weapons in the stockpile
 - By treaty, there are no underground nuclear test detonations



Science-Based Stockpile Stewardship Leads to Predictive Computational Science

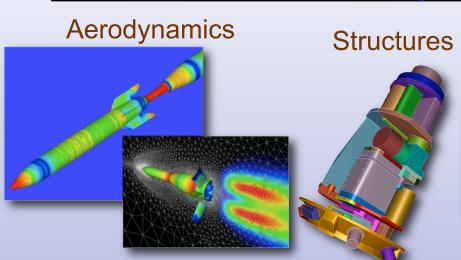
- Problems with a solely testing-based approach
 - Eventually you run out of weapons to test
 - Without underground testing, you can't test the complete system
 - Not predictive
- Science-based stockpile stewardship
 - Develop comprehensive scientific models to assess safety, security, reliability of weapons
 - Understand how materials age
 - Effects of abnormal environments (heat, radiation, etc...)
 - Effects of imperfections, impurities, etc...
 - Using
 - Testing
 - Experimentation
 - Modeling
 - Computation

Predictive Computational Science

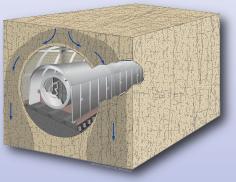




A Sampling of Areas of Interest for **Predictive Computational Science**





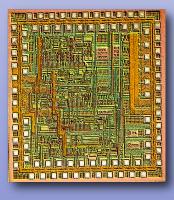


MEMS

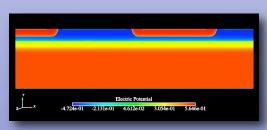


Combustion

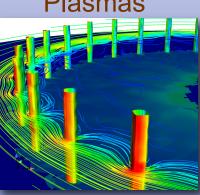


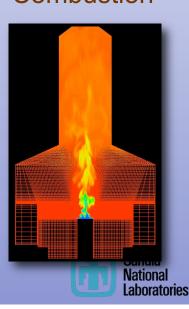


Semiconductors



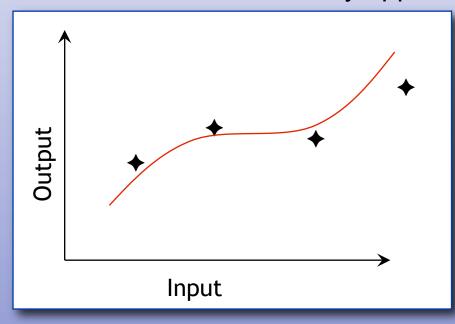
Plasmas

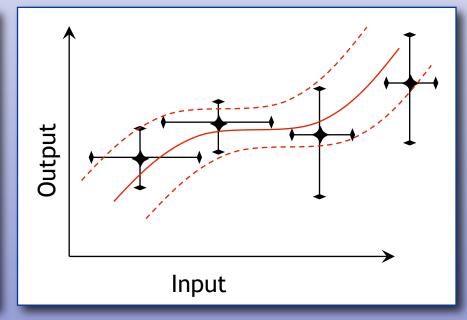




What Does "Predictive Computational Science" Mean?

- A scientifically credible and justifiable statement that a computation is capable of adequately capturing a physical/natural process.
 - Expert opinion is not sufficient
 - This was not readily apparent to the original ASC program





Verification, Uncertainty Quantification and Validation





Verification

- The process of determining that a model implementation accurately represents the developer's conceptual description of the model and the solution to the model.
 - "Are the equations solved correctly?"
- Code verification:
 - Finding and removing source code mistakes (bugs)
 - Improving software using software quality assurance practices (SQA)
- Solution verification:
 - Estimating numerical solution error
 - Grid refinement studies
 - Method of manufactured solutions
 - A posteriori error estimation
 - Assuring accuracy of simulation input and output data





- Process for determining how incomplete knowledge or variability of simulation inputs impact simulation results
 - Characterization of input uncertainties
 - Propagation of uncertainties through simulation to outputs
- Epistemic uncertainty -- "Lack of knowledge"
 - Set representations
 - Interval arithmetic
 - Possibility/Evidence theory
- Aleatory uncertainty -- "Intrinsic variability"
 - Probabilistic representations
 - Monte Carlo sampling and its many variants (LHS, importance,...)
 - Stochastic collocation
 - Polynomial chaos and other "spectral" projections





Validation

- The process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model.
 - "Are we solving the correct equations?"
- Comparison of computational predictions to experimental observations
 - Quantitative assessment of experimental errors
 - Quantitative assessment of total computational error (numerical error + uncertainty)
 - Identification of a metric indicating whether simulation and experiment "agree"





So What's the Problem?

- V&V + UQ define a formal process for justifying predictive capability
 - Doesn't say how to do it
 - Doesn't say what to do when it doesn't work
 - May not understand the physics
 - May not be able to simulate at necessary level of fidelity
 - May not be able to measure all uncertainties/errors
 - May not have enough data
- Clearly significant challenges must be overcome
 - Accurate and efficient error estimation
 - Efficient uncertainty propagation for
 - strongly nonlinear problems
 - problems with discontinuities over parameter domain
 - Design of validation metrics



Transformation to Predictive Science

- Computers, Computation, Information, and Mathematics Center (CCIM) is trying to lead transformation to predictive science at Sandia
 - Algorithms research
 - Incorporating state-of-the-art algorithms in production physics simulation codes
- Obtaining accurate derivatives efficiently has been one of the most significant hurdles
 - Focusing on Automatic Differentiation as a general technique for getting derivatives out of application codes



What Do Derivatives Have To Do With Predictive Science

- Verification
 - Adjoint-based error estimation
 - Sensitivity analysis to identify dominant physics
- Uncertainty quantification
 - Taylor expansions for uncertainty propagation
 - Identifying bifurcations for failure modes
 - Inverse problems for deducing uncertainty representations based on data
 - Optimization under uncertainty
- Validation
 - Adjoint-based parameter estimation and model calibration



Automatic Differentiation is an Enabling Technology for Predictive Science

- Analytic derivatives improve robustness and efficiency
 - -Very hard to make finite differences accurate
- Infeasible to expect application developers to code analytic derivatives
 - -Time consuming, error prone, and difficult to verify
 - -Thousands of possible parameters in a large code
 - Developers must understand what derivatives are needed
- Not having analytic derivatives has been significant hurdle to predictive science research
- Automatic differentiation solves these problems



What is Automatic Differentiation (AD)?

- Technique to compute analytic derivatives without hand-coding the derivative computation
- How does it work -- freshman calculus
 - Computations are composition of simple operations (+, *, sin(), etc...)
 with known derivatives
 - Derivatives computed line-by-line, combined via chain rule
- Derivatives accurate as original computation
 - No finite-difference truncation errors
- Provides analytic derivatives without the time and effort of hand-coding them

$$y = \sin(e^x + x \log x), \ \ x = 2$$

		x	$\frac{d}{dx}$
$x \leftarrow 2$	$\frac{dx}{dx} \leftarrow 1$	2.000	1.000
$t \leftarrow e^x$	$\frac{dt}{dx} \leftarrow t \frac{dx}{dx}$	7.389	7.389
$u \leftarrow \log x$	$\frac{du}{dx} \leftarrow \frac{1}{x} \frac{dx}{dx}$	0.301	0.500
$v \leftarrow xu$	$\frac{dv}{dx} \leftarrow u\frac{dx}{dx} + x\frac{du}{dx}$	0.602	1.301
$w \leftarrow t + v$	$\frac{dw}{dx} \leftarrow \frac{dt}{dx} + \frac{dv}{dx}$	7.991	8.690
$y \leftarrow \sin w$	$\frac{dy}{dx} \leftarrow \cos(w) \frac{dw}{dx}$	0.991	-1.188





How is AD Implemented?

Source transformation

- Preprocessor implements AD
- Very efficient derivative code
- Works well for FORTRAN, some C
- Extremely difficult for C++
- OpenAD, ADIFOR, ADIC (Argonne National Lab & Rice University)

Operator overloading

- All intrinsic operations/elementary operations overloaded for AD data types
- Change data types in code from floats/doubles to AD types
 - C++ templates greatly help
- Easy to incorporate into C++ codes
- Slower than source transformation due to function call overhead
- ADOL-C (TU-Desden), Sacado (Sandia), MAD (matlab)



How is AD Used In Computational Science?

- Most AD uses have focused on black-box application
 - –Trying to live up to the name "automatic"
- AD is better used selectively as a software engineering tool
 - Only use AD for the hard nonlinear parts
 - -Don't use AD on solvers

Spatially discretized PDE:

$$f(\dot{u},u,p,t)=0$$

Temporal discretization (Backward Euler):

$$f\left(rac{u_n-u_{n-1}}{\Delta t},u_n,p,t_n
ight)=0$$

Forward sensitivity problem:

$$rac{\partial f}{\partial \dot{u}} \left(rac{\partial \dot{u}}{\partial p}
ight) + rac{\partial f}{\partial u} \left(rac{\partial u}{\partial p}
ight) + rac{\partial f}{\partial p} = 0$$

$$rac{1}{\Delta t}rac{\partial f}{\partial \dot{u}}\left(rac{\partial u_n}{\partial p}-rac{\partial u_{n-1}}{\partial p}
ight)+rac{\partial f}{\partial u}\left(rac{\partial u_n}{\partial p}
ight)+rac{\partial f}{\partial p}=0$$

Element decomposition:

$$f(\dot{u},u,p,t) = \sum_{i=1}^N Q_i^T e_{k_i}(P_i \dot{u},P_i u,p,t)$$

$$rac{1}{\Delta t}rac{\partial f}{\partial \dot{u}}+rac{\partial f}{\partial u}=\sum_{i=1}^{N}Q_{i}^{T}\left(rac{1}{\Delta t}rac{\partial e_{k_{i}}}{\partial \dot{u}_{i}}+rac{\partial e_{k_{i}}}{\partial u_{i}}
ight)P_{i}$$

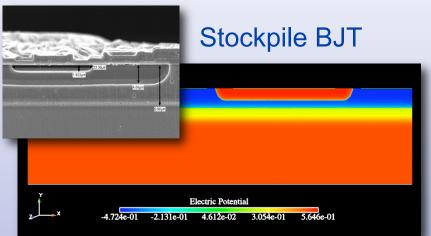




QASPR

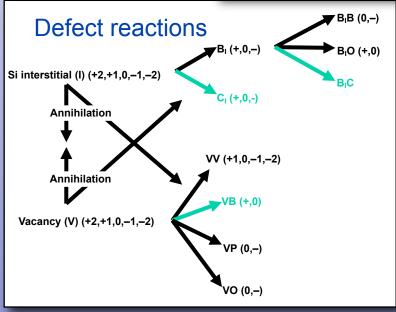
Qualification of electronic devices in hostile environments

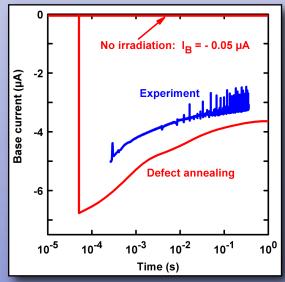






PDE semiconductor device simulation

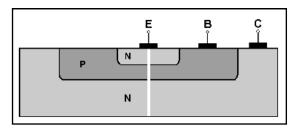


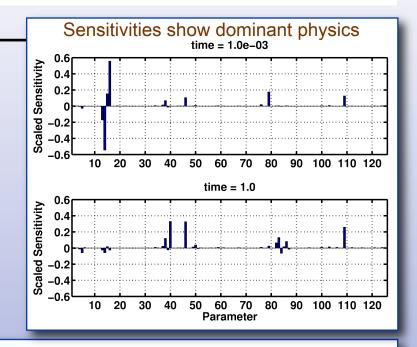


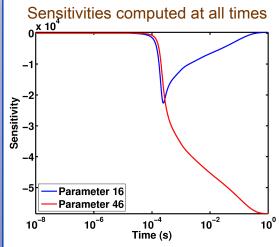


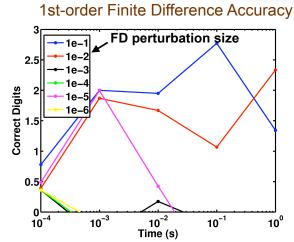
Transient Sensitivity Analysis of a Bipolar Junction Transistor Under Radiation

- Bipolar Junction Transistor
- Pseudo 1D strip (9x0.1 micron)
- Full defect physics
- 126 parameters







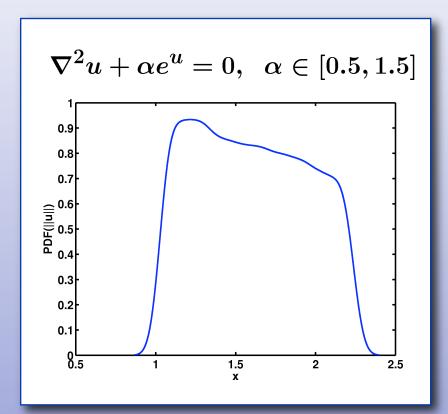


Comparison to FD:

- ✓ Sensitivities at all time points
- ✓ More accurate
- ✓ More robust
- √ 14x faster!

Moving Beyond Forward Sensitivities

- We are building on this technology for
 - Adjoint sensitivities
 - Second derivatives (SQP optimization)
 - Taylor polynomials (Time integration, UQ)
- We are also investigating ADlike ideas for calculations beyond derivatives
 - Polynomial chaos expansions for UQ





Educational Needs and Opportunities

- Must change culture for predictive computational science to be successful
 - -Single-point forward simulations are not sufficient
- By emphasizing these ideas in undergraduate/graduate education, we can get there
- AD in particular is proving to be an important piece of the solution
- Significant progress could be made by exposing AD early in undergraduate education/research
 - -Prerequisites are basic calculus and programming skills



AD Takes Two Basic Forms

$$x \in \mathbb{R}^n$$
, $f: \mathbb{R}^n \to \mathbb{R}^m$, $y = f(x) \in \mathbb{R}^m$

- Forward Mode:
 - Propagate derivatives of intermediate variables w.r.t. independent variables forward

$$c = \varphi(a,b) \implies \frac{\partial c}{\partial x_i} = \frac{\partial \varphi}{\partial a} \frac{\partial a}{\partial x_i} + \frac{\partial \varphi}{\partial b} \frac{\partial b}{\partial x_i}$$

Change of variables

$$x = Vz, \;\; V \in \mathbb{R}^{n imes p} \implies rac{\partial y}{\partial z} = rac{\partial f}{\partial x} V$$

Complexity

$$\mathsf{ops}\left(f,\,rac{\partial f}{\partial x}V
ight)pprox(1+1.5p)\mathsf{ops}(f)$$

- Reverse Mode:
 - Propagate derivatives of dependent variables w.r.t. intermediate variables backwards

$$c = \varphi(a,b) \implies rac{\partial y_j}{\partial a} = rac{\partial y_j}{\partial c} rac{\partial arphi}{\partial a}, \;\; rac{\partial y_j}{\partial b} = rac{\partial y_j}{\partial c} rac{\partial arphi}{\partial b}$$

- Change of variables

$$z = W^T y, \;\; W \in \mathrm{R}^{m imes q} \implies rac{\partial z}{\partial x} = W^T rac{\partial f}{\partial x}$$

Complexity

$$\mathsf{ops}\left(f,\;W^Trac{\partial f}{\partial x}
ight)pprox (1.5+2.5q)\mathsf{ops}(f)$$



Charon Drift-Diffusion Formulation with Defects

Current Conservation for eand h+

$$\frac{\partial n}{\partial t} - \nabla \cdot J_n = -R_n(\psi, n, p, Y_1, \dots, Y_N), \quad J_n = -n\mu_n \nabla \psi + D_n \nabla n$$

$$\frac{\partial p}{\partial t} + \nabla \cdot J_p = -R_p(\psi, n, p, Y_1, \dots, Y_N), \quad J_p = -p\mu_p \nabla \psi - D_p \nabla p$$

$$rac{\partial t}{\partial \mathbf{V}}$$

$$\frac{\partial p}{\partial t} + \nabla \cdot J_p = -R_p(\psi, n, p, Y_1, \dots, Y_N), \quad J_p = -p\mu_p \nabla \psi - D_p \nabla p$$

Defect Continuity
$$\frac{\partial Y_i}{\partial t} + \nabla \cdot J_{Y_i} = -R_{Y_i}(\psi, n, p, Y_1, \dots, Y_N), \quad J_{Y_i} = -\mu_i Y_i \nabla \psi - D_i \nabla Y_i$$

Recombination/ generation source terms

 R_{X}

Include electron capture and hole capture by defect species and reactions between various defect species

Electron emission/ capture

$$Z^i \leftrightarrow Z^{i+1} + e^-$$

$$R_{[Z^i o Z^{i+1}+e^-]} \propto \sigma_{[Z^i o Z^{i+1}+e^-]} Z^i \exp\left(rac{\Delta E_{[Z^i o Z^{i+1}+e^-]}}{kT}
ight)$$

Cross section

